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ANALYSIS AND EVALUATION OF MACHINING RESPONSES DURING HARD TURNING OF EN353 STEEL

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ABSTRACT

Estimation, prediction and analysis of responses in turning operation is one of the key research areas. This paper studies the performance of coated inserts (PVD and CVD) in hard machining. In this analysis, 27sets of hard turning experimental trials were performed on a plain turning lathe to study the effect of cutting parameters in influencing the machined surface roughness, material removal rate and power consumption. In all the trials, EN353steel work piece (hardness up to 62 HRC) was machined with commercially available carbide inserts under dry conditions. The machining outcome was used as an input to develop regression models to predict the machined responses on this material. The analysis of this model was used to develop Multi-Objective equation within the specified range of constraints to ascertain the influence of cutting speed, spindle feed and depth of cut to correlate these variables on the stated responses. It was concluded that the multi linear regression model is a choice for prediction of machining responses during machining of EN353 steel (62 HRC) and the results are effective and comparable with Genetic Algorithm (GA) and Artificial Neural Networks (ANN).

KEYWORDS: Multi Objective Optimization, Hard Turning, Regression Analysis & GA, ANN

Original Article

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INTRODUCTION

Turning is one such basic machining process in which the work-piece is rotated at a particular speed (cutting speed) and the tool is fed against the work piece (feed) at a certain level of engagement(depth of cut). Essentially, the combination matrix of these three parameters is of critical importance in determining the outcome of the machining process. Proper selection of these three parameters is an essential step to make the process more accurate in terms of the machined quality of the component and other favorable outcomes Hard turning differs from conventional turning on account of a number of factors including the cutting tool, work piece, or the process itself, all of which may influence the machining outcomes. En353 steel is used very frequently to manufacture critical components in aerospace engineering and automotive transmissions, including the manufacture of gears, shafts, and cams, which require tighter geometric tolerances, longer service life, and good surface finish. The primary focus of this work is to investigate the influence of various machining parameters affecting the machined responses. Some of the major studies found in the literature pertaining to the optimization of hard turning are tabulated in Table 1.It can be seen from this table that limited studies are attempted to optimize the hard turning of 702 BHN hardened EN353 steel with carbide inserts, whereas it is very clear from the literature that work piece hardness could be an important variable in influencing the machined responses.

LITERATURE REVIEW

Hasan Gokkaya and Muammer Nalbant.,(2006) [1], studied the effects of a number of cutting tool coating materials on surface quality of AISI1015 work pieces without cooling by PVD and CVD cutting tools. His findings reflected that the coating type, feed rate, cutting speed have different effects on the surface roughness. S. Bharathi Raja and N. Baskar (2010) [2], Studied the behavior of optimization techniques based on various mathematical models. The success of machining operations mainly depends on the selection of machining parameters such as cutting speed, feed and depth of cut. As per B. Y. Lee and Y. S. Tarng 2000 [3], optimal selection of cutting parameters considering the economics of multistage turning operations, reported that the developed networks have reasonable accuracy for modeling turning operations with the error between the predicted and measured responses is less than 10%. M. Y. Noordin, et al., 2004 [4], reported the performance of a multilayer tungsten carbide tool using RSM when turning AISI 1045 steel. They investigated cutting speed, feed and side cutting edge angle of the cutting edge on main cutting force and surface roughness. Their findings was that the level of deformation of the chips is very low when the tool with -5˚SCEA is being used at low feed rate. From the investigations of T. Srikanth and V. Kamala, 2008 [5], it is stated that the machining process parameter optimization is highly constrained and nonlinear. They proposed real coded genetic algorithm to find the optimum cutting parameters. C. Natarajan, et al, 2011 [6], found a suitable optimization method which can find optimum values of cutting parameters for minimizing surface roughness. The turning process parameter optimization is highly constrained and nonlinear. To predict the surface roughness, an artificial neural network (ANN) model was designed through back propagation network using MATLAB 7 software for the data obtained. K. V. V. Chandra Mouli, et.al, (2006)[7] Proposed an approach based on Taguchi’s method to predict the optimum process parameters and forecasts the outputs at these parameters using Neural networks. The concept of Taguchi design together with neural network was analyzed for pig iron and an accuracy within 5% was established According to V.V.K. Lakshmi, and K. Venkata Subbaiah (2012) [8], utilized response surface methodology for optimizing the cutting parameters during end milling of EN24 steel. The results thus obtained were used to develop a second order quadratic model to predict surface roughness. Mulla Kaladhar et.al.,(2012)[9], reported on investigations with respect to the effects of process parameters on surface finish and material removal rate by Taguchi’s approach. ANOVA was used to analyze the influence to cutting parameters. PVD coated tool was used on stainless steel work piece. The results revealed that feed and nose radius were the most significant process parameters for surface roughness. Depth of cut and feed are significant for MRR. Optimal range and optimal level of parameters are also predicted for the responses. Hari Singh and Pradeep Kumar (2006) [10] used Taguchi’s parameter design approach to obtained an optimal setting of turning process parameters resulting in an optimal value of feed force when machining EN24 steel with coated tungsten carbide inserts. Hrelja Marko et.al (2014)[11], presented a proposal, for optimal cutting parameters – cutting speed, feed rate and cutting depth for requirements such as cutting force, surface finish – roughness and cutting tool life to assure cheaper products, shorter manufacturing times, lowering of the production costs. He provided for initial step into optimizing methods and it shows an elementary approach to solving machining optimization parameters. Harsh Y Valera and Sanket N Bhavsar (2014)[12], presented experimental results of power consumption and roughness characteristics of surface generated in turning operation of EN-31 alloy steel with TiN+Al2O3+TiCN coated tungsten carbide tool under different cutting parameters. The study shows the influences of three cutting parameters like spindle speed, depth of cut and feed rate affecting surface roughness as well as power consumption while turning operation of EN-31 alloy steel. They concluded that spindle speed, feed and depth of cut significantly affect the surface roughness and power consumption while tuning EN 31 alloy steel work material using

coated carbide cutting tool. To optimize the cutting parameters for achieving better surface finish with reduced power consumption detailed design of experimentation is needed for the work piece material under investigation. B. Anuja Beatrice et.al (2014)[13], attempted to investigate, and develop a model based on Artificial Neural Network to simulate hard turning of AISI H13 steel with minimal cutting fluid application. This model was developed to predict the surface roughness in terms of cutting parameters. The ability of ANN model to predict surface roughness (Ra) was analyzed. It was found that the predictions made by the ANN model matched well with the experimental results. Coefficient of determination and standard error were chosen as performance indices for evaluating the ability of the models to predict surface roughness. It was also observed with ANN model that the prediction with considerable accuracy (error percentage of < 7%) is possible even with smaller number of training data. B.Singarvel et.al(2014)[14], In this experimental analysis the optimum machining parameters are estimated using Taguchi based utility concept coupled with Principal Component Analysis (PCA) on turning of EN25 steel with CVD and PVD coated carbide tools. This method has been employed for simultaneous minimization of surface roughness, cutting force and maximization of material removal rate. ANOVA concept is employed on multi SN ratio to find out the relative significance of machining parameter in terms of their percentage contribution. These weighting factors are calculated using PCA for the various objectives to be simultaneously optimized in multi objective optimization, weight criteria of each objective is considered for producing better and accurate solutions. Anupam Agrawal et.al (2015) [15], conducted experiments to study the effect of cutting parameters in influencing the machined surface roughness. AISI 4340 steel work piece was machined with CBN insert under dry conditions. The machining outcome was used as an input to develop various regression models to predict the average machined surface roughness on this material. For the first time, the random forest regression modeling has been applied to the machining domain and an excellent correlation has been found between the model and the in-house experimental results. Multiple regression models obtained from in-house trials revealed the mathematical equations which could respectively provide 92.5%and 95% accurate predictions of average value of machined surface roughness compared with the experimental results. Sunil Dambhare et.al [16], highlighted that manufacturing industries that are crucial for country's economy account for huge resource consumption and waste excretion. Sustainable issues pertaining to turning process in Indian machining industries was studied with specific reference to input and output parameters. The effect of process parameters such as (speed/feed/depth of cut), machining environment (dry/MQL/wet) and the type of cutting tool was observed on the stated responses. The results of the study helped to study the effect of cutting parameters on surface finish, energy consumption, and material removal rate. The process was optimized from power consumption point of view. Mozammel Mia and Nikhil Ranjan Dhar (2016)[17], conducted investigations to predict surface roughness by artificial neural network (ANN) predictive model in turning hardened EN 24T steel. The prediction was performed by using Neural Network Tool Box 7 of MATLAB R2015a for different levels of cutting speed, feed rate, material hardness and cutting conditions. A good prediction fit of the models was established by the regression coefficients. The best predictive model was recommended only after evaluating the prediction capability of different neural network architectures and various training method. D.M. D'Addona, and Sunil J Raykar (2016) [18], according to the authors hard turning process is currently replacing the conventional grinding operations in many industries. If properly designed, hard turning can give equivalent results to grinding process in terms of accuracy and machined surface quality. They investigated the performance of wiper inserts in hard turning of oil hardening non-shrinking steel. Influence of process parameters such as speed, feed, depth of cut and nose radius (for wiper and conventional inserts) on surface roughness is analyzed using analysis of variance (ANOVA) and analysis of means (AOM) plots. From the analysis, it was clearly shown that wiper inserts produced a very good machined surface compared to conventional inserts. Philippe Revel et.al (2016)[19], In their

research findings they proposed precision hard turning for the finishing of AISI 52100 bearing components and found that increasing cutting speed leads to increase the level of compressive residual stresses. The precision turning of hard steel AISI 52100 allows to obtain low surface roughness and to improve the surface integrity. These improvements of the machined surfaces increase their life-time when they are solicited in fatigue.

EXPERIMENTAL DETAILS AND ANALYSIS

The chemical composition for the chosen work material is given in the table 2 with diameter Ø50 mm and length 500 mm. The dimensions of the specimen were selected to minimize deflection by the chucking forces of a standard jaw and to be uniformly through hardened. The tool post is connected to lathe tool dynamometer for determining of cutting forces. The surface roughness is measured after end of each cut by using Mitutoyo Surface Roughness Tester (SJ-201 P) Stylus type (Mitutoyo Corporation, Japan) make.

Table 1: Composition (%) of Specimens

Element	Composition
C	0.17
Si	0.19
Mn	0.6
S	0.04
P	0.04
Cr	0.92
MO	0.1
Ni	1.03

Table 2: Composition of Selected CVD and PVD Coated Inserts

Type	Grade	Composition	Density (kg/m^3)	Hardness BHN	Fracture Toughness
CVD	CA 5515	$TiCN+Al_2O_3+TiN$	14.5	802	12GPa
PVD	PR1125	Ti Al N	14.5	997	13GPa

Table 3: Different Operating Parameters and their Levels Used for EN 353 Steel

S. No	Operating Parameters	Levels of Parameters		
		Level -1	Level - 2	Level-3
1	Speed (rpm)	740 (V_1)	580 (V_2)	450(V_3)
2	Cutting feed (F) (mm/rev)	0.09(F_1)	0.07 (F_2)	0.05(F_3)
3	Depth of cut (D) (mm)	0.25(D_1)	0.2(D_2)	0.1(D_3)

Table 4: Influential Parameters on Stated Responses for CVD Insert

CVD	Influencing Parameter		Optimum Levels SNR	Speed(v)	Feed(f)	DOC(d)
	SNR	ANVOA				
Ra	DOC	DOC	3-3-3	450	0.05	0.1
MRR	Cutting Speed	Cutting Speed	1-3-2	740	0.05	0.2
Power Consumed	DOC	DOC	3-1-3	450	0.09	0.1

Table 5: Influential Parameters on Stated Responses for PVD Insert

PVD	Influencing Parameter		Optimum Levels SNR	Speed(v)	Feed(f)	DOC(d)
	SNR	ANVOA				
Ra	DOC	Cutting Speed	1-3-1	740	0.05	0.25
MRR	Cutting Speed	Cutting Speed	3-3-2	450	0.05	0.2

Table 5: Contd.,

Power Consumed	Cutting Speed	Cutting Speed	2-1-1	580	0.09	0.25

Regression Analysis

On the analysis of the literature reviews most of the researchers considered second order quadratic equation for Surface roughness (Ra), Material removal rate (MRR) and power consumed (PC) were chosen. In developing the surface roughness, MRR and power consumed (PC) models the determination of constant (k) and coefficients a,b,c and parameters the mathematical models were linear zed by performing Logarithmic transformations converting into a linear modeling using computational software. The following equations for three parameters were obtained as shown in below.

The relationship between the surface roughness and machining independent variables (speed, feed and depth of cut) are shown by the following:

$$F(y) = k\, s^{a} f^{b} d^{c}. \tag{1}$$

Where, Ra is the surface roughness in µm, MRR is material removal rate; PC power consumption s, f and d are the cutting speed, feed and depth of cut respectively. K, a, b and c are constants. In order to facilitate the determination of constants and parameters, the mathematical models were linearized by performing logarithmic transformation as follows:

$\ln Ra = \ln K + a \ln S + b \ln f + c \ln d$

The linear model of the above equation in terms of estimated response can be written as:

$y = b_{0}\,_{x0} + b_1 x_1 + b_2 x_2 + b_3 x_3$

Where 'y' is the logarithmic value of the measured response,

x_0 =1(unit vector),

x1=*ln* S,

x2=*ln* f, and

x3=*ln* d and" $b_{0,1,2,3}$" values are the estimates of the model parameters.

Objective functions for EN 353 on PVD:

Minimising $Ra = 1.5054\ S^{0.255}\ f^{-0.0410}\ d^{0.471}$ (1)

Maximising $MRR = 0.004992\ S^{1.08}\ f^{0.283}\ d^{1.20}$ (2)

Minimisation $PC = 0.000034\ S^{1.79}\ f^{-0.409}\ d^{0.175}$ (3)

Objective functions for EN 353 on CVD tool:

Minimizing R_a (s, f, d) $= 0.07\, S^{0.218}\ f^{-0.23} d^{0.233}$ (4)

Maximizing MRR (s, f, d) $= -11.0\ S^{1.76}\ f^{0.110} d^{0.586}$ (5)

Minimizing PC (s, f, d) $= -10.4\ S^{1.79}\ f^{-0.409} d^{0.175}$ (6)

Constraints

$V_{min} \leq V \leq V_{max}$, $450 \leq V \leq 740$ (7)

$qf_{min} \leq f \leq f_{max}$, $0.05 \leq f \leq 0.09$ (8)

$d_{min} \leq d \leq d_{max}$, $0.10 \leq d \leq 0.25$ (9)

Genetic Algorithm (GA) and Artificial Neural Networks (ANN)

The GA is used to estimate the combination of the values of depth of cut, speed, and feed that minimize the value of surface roughness, Power consumption and maximize material removal rate.

As the crossover depends on the idea that good parents should give good child, one or more child is generated from combinations of two parents. In this paper one point cross over is used, in which a random point is selected randomly on the two parents. These random points split parents into two part, head and tail. Child is formed by exchange the tail of the two parents. In this paper scramble mutation is used, in which a random point on one parent is chosen. After this point the arrangement of the genes in the chromosome is changed.

Fitness function is used to assess the performance of the individual. Based on their fitness, parents are selected to reproduce offspring for a new generation. In this paper the fitness function deduced using regression equations.

The condition used for stopping criteria is when the algorithm reaches a specified number of generations.

For prediction of Ra, MRR and PC linear logarithmic equations are developed and deviation is observed to be minimum and hence, these equations are considered as objectives in GA.

For optimal cutting conditions multi objective function along with weights are considered. These weight functions are selected randomly such that the summation of weights is equal to 1.

Multi Objective Function

$$\mathbf{Y = W_1 * 1/Ra(s,f,d) + W_2 * MRR(s,f,d) + W_3 * 1/PC(s,f,d)} \quad (10)$$

Where W1, W2, W3 are the entropy assigned weights subject to condition that W1+ W2 +W3 = 1

Table 6: Optimal Cutting Conditions and Response Values for Different Weighting Factors (PVD)

S. No	Weights			Optimal cutting condition levels			GA		
	W1	W2	W3	Speed (V)	Feed (F)	DOC (D)	Ra (μm)	MRR (Kg/min)	Power Consumed (Watts)
1	0.104	0.393	0.503	729.979	0.089	0.249	4.353	0.655	7.449
2	0.393	0.503	0.104	666.744	0.087	0.249	4.220	0.594	7.185
3	0.503	0.104	0.393	734.541	0.086	0.248	4.344	0.648	7.500
4	0.393	0.104	0.503	676.921	0.09	0.25	4.251	0.611	7.212
5	0.104	0.503	0.393	725.321	0.089	0.249	4.344	0.652	7.429
6	0.503	0.393	0.104	734.998	0.089	0.249	4.362	0.660	7.470

Table 7: Optimal Cutting Conditions and Response Values for different Weighting Factors (CVD)

S. No	Weights			Optimal cutting condition levels			GA		
	W1	W2	W3	Speed (V)	Feed (F)	DOC (D)	Ra (µm)	MRR (Kg /min)	Power Consumed (Watts)
1	0.078	0.374	0.548	738.472	0.090	0.250	3.258	0.635	8.711
2	0.374	0.548	0.078	732.584	0.090	0.250	3.252	0.627	8.587
3	0.548	0.078	0.374	739.995	0.090	0.249	3.256	0.636	8.737
4	0.374	0.078	0.548	736.587	0.090	0.250	3.256	0.633	8.674
5	0.078	0.548	0.374	705.600	0.09	0.250	3.226	0.587	8.028
6	0.548	0.374	0.078	720.705	0.09	0.250	3.241	0.609	8.338

Table 8: GA Verses ANN Surface Roughness (Ra) Values-(PVD)

S. No	Weights			Optimal Cutting Conditions			GA Ra (µm)	ANN Ra (µm)
	W1	W2	W3	Speed (F)	Feed (F)	DOC (D)		
1	0.104	0.393	0.503	729.979	0.089	0.249	4.353	4.535
2	0.393	0.503	0.104	666.744	0.087	0.249	4.220	4.473
3	0.503	0.104	0.393	734.541	0.086	0.248	4.344	4.524
4	0.393	0.104	0.503	676.921	0.09	0.25	4.251	4.491
5	0.104	0.503	0.393	725.321	0.089	0.249	4.344	4.532
6	0.503	0.393	0.104	734.998	0.089	0.249	4.362	4.537

Table 9: GA Verses ANN Material Removal Rate (MRR) Values (CVD)

S. No	Weights			Optimal Cutting Conditions			GA MRR (Kg /min)	ANN MRR (Kg /min)
	W1	W2	W3	Speed (v)	Feed (f)	DOC (d)		
1	0.078	0.374	0.548	738.472	0.090	0.250	0.635	0.624
2	0.374	0.548	0.078	732.584	0.090	0.250	0.627	0.603
3	0.548	0.078	0.374	739.995	0.090	0.249	0.636	0.625
4	0.374	0.078	0.548	736.587	0.090	0.250	0.633	0.619
5	0.078	0.548	0.374	705.600	0.09	0.250	0.587	0.509
6	0.548	0.374	0.078	720.705	0.09	0.250	0.609	0.559

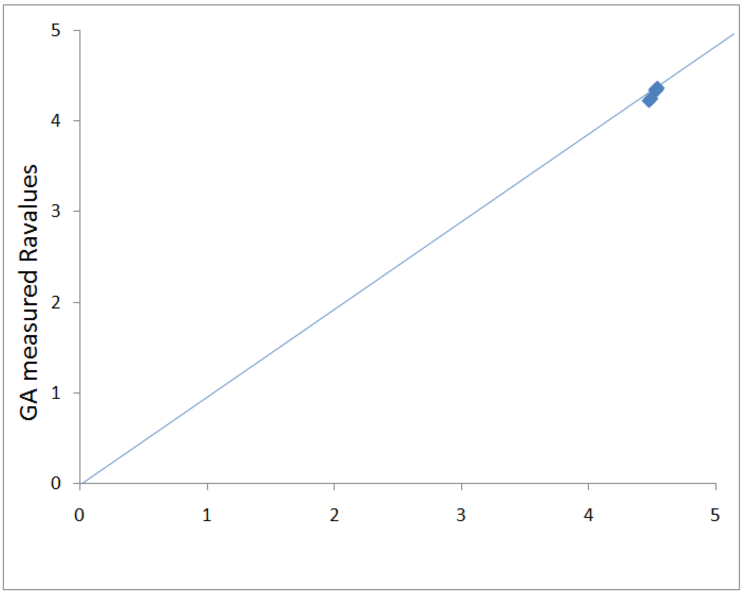

Figure 1: GA Verses ANN Surface Roughness (Ra) Values

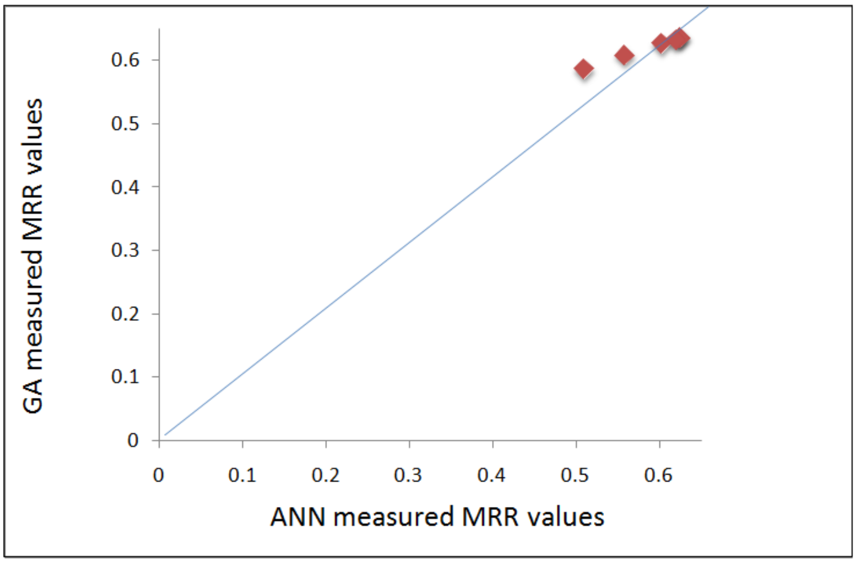

Figure 2: GA Verses ANN Material Removal Rate (MRR)

CONCLUSIONS

- The experimental results in turning EN353 steel using PVD and CVD coated tools on surface roughness showed that, the depth of cut is most influencing parameter.
- The influencing parameter of metal removal rate on EN353 steel for both PVD and CVD tools is on speed.
- Similarly of power consumption the most influence parameter is speed for PVD tool whereas for CVD tool it is depth of cut
- It is also observed from the ANOVA that there is no coincidence of levels of operating cutting conditions for better surface, Surface Roughness and maximum Metal Removal Rate and minimum Power Consumption

The results of GA on PVD shows that for the weights W1 = 10.4%; W2 = 39.3%; W3 = 50.3%; i.e. Minimization of power consumption is the highest priority, which shows the optimum conditions of 730 RPM of speed; Feed 0.09mm/min and 0.25mm of Depth of cut for which the predicted surface roughness is 4.353µm; 0.656 kg/min of MRR; and 7.45W of power consumption.

The optimum values of GA results for this level is simulated in ANN, shows an approximate deviation of 4% from the actual GA value for Ra & MRR and 10% deviation for Power consumption.

Another set of results of GA on CVD shows that for the weights W1 = 37.4%;W2 = 54.8%; W3 = 7.8%; i.e. Maximization of MRR is the highest priority, which shows the optimum conditions of 733 RPM of speed; Feed 0.09mm/min and 0.25mm of Depth of cut for which the predicted surface roughness is 3.252µm; 0.6265 kg/min of MRR; and 8.586W of power consumption.

The optimum values of GA results for this level are simulated in ANN, which shows an approximate deviation of 0.4%, 3.81% and 1.82% from the actual GA value of Ra, MRR and PC.

Power consumption is observed to be deviating for the following significant reasons

- Fluctuations in supply of voltage

- Variation in cutting forces
- Friction between tool and work-piece.
- Uncontrollable factors beyond operators control.

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